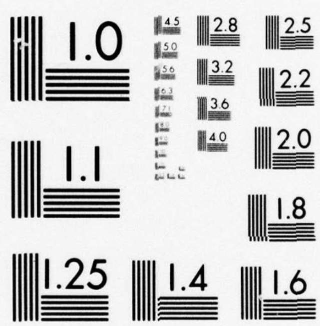
AD-A040 598 GEORGIA INST OF TECH ATLANTA COLL OF INDUSTRIAL MAN--ETC F/G 12/2
WHERE HAVE ALL THE MODERATORS GONE: THE PERILS OF TYPE II ERROR--ETC(U)
MAY 77 M R BLOOD, G M MULLET N00014-76-C-0828
UNCLASSIFIED GIT-M-77-5 NL

1 OF 1
AD A040 598

END
DATE FILMED
7-77



MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

COLLEGE OF INDUSTRIAL MANAGEMENT
GEORGIA INSTITUTE OF TECHNOLOGY
ATLANTA, GEORGIA 30332

Where Have All the Moderators Gone?:

The Perils of Type II Error

Milton R. Blood

Gary M. Mullet

College of Industrial Management
Georgia Institute of Technology

Technical Report #1
M-77-5 (Working Paper Series)

This research was sponsored by the Organizational Effectiveness Research Program, Office of Naval Research (Code 452), under Contract No. N00014-76-C-0828; NR 170-828

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER TR #1	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) (6) WHERE HAVE ALL THE MODERATORS GONE: THE PERILS OF TYPE II ERROR.		5. TYPE OF REPORT & PERIOD COVERED (9) Technical ~~Report~~.
		6. PERFORMING ORG. REPORT NUMBER M-77-5
7. AUTHOR(s) (10) Milton R. /Blood Gary M. /Mullet		8. CONTRACT OR GRANT NUMBER(s) (15) N00014-76-C-0828
9. PERFORMING ORGANIZATION NAME AND ADDRESS Georgia Institute of Technology College of Industrial Management Atlanta, GA 30332		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS NR 170-828
11. CONTROLLING OFFICE NAME AND ADDRESS Organizational Effectiveness Research Programs Office of Naval Research (Code 452) Arlington, VA 22217		12. REPORT DATE (11) May 1977
		13. NUMBER OF PAGES 22
14. MONITORING AGENCY NAME & ADDRESS (If different from Controlling Office) (12) 25p.		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release: distribution unlimited.

(14) GIT-M-77-5, TR-1

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Hierarchical regression	Multiple correlation
Interaction effect	Statistical power
Linear effect	Statistical significance
Moderated regression analysis	Type II error
Moderator effect	

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Traditional moderated regression analysis requires a significant and sizable increment in R^2 due to the interaction term in order to conclude that there is a moderator effect. A Monte Carlo analysis demonstrates that the traditional procedure will not discover moderators even when they are the only existing effect. A suggestion is made to reverse the usual hierarchical order of the moderated regression analysis. The choice between a linear and an interactive model should be made on the basis of theoretical justification.

DD FORM 1473 EDITION OF 1 NOV 65 IS OBSOLETE Unclassified

Dep 315 0
38389
9d15693

Where Have All the Moderators Gone?:

The Perils of Type II Error

Moderated regression analysis has been used in psychological research since its presentation by Saunders (1956). This technique assesses the influence of a third variable, called a moderator, on the relationship between two other variables. Knowledge of the level of the moderator variable provides information about the strength of the relationship between the other two variables. In his explication of the procedure, Saunders pointed out that a moderator effect will manifest itself as a relationship between the dependent variable and the cross product of the independent and moderator variables. Conceptually, this is equivalent to saying that the relationship between the dependent and independent variables is influenced by the moderator variable.

The relationship thus described allows the postulation of individual differences in the relationships between variables, i.e., one could hypothesize that the relationship between two variables is stronger for individuals who are high on a third characteristic than for individuals who are low on the third characteristic. For example, in the original article Saunders (1956) tested the hypothesis that the relationship between the Engineer Scale of the Strong Interest Blank (independent variable) and the grade point average (dependent variable) of engineering freshman is higher for non-compulsive (moderator variable) students than for compulsive students. This pattern of interrelationships among variables has widespread usefulness in model building. As stated by Saunders (1956), "The class of situations in which the 'moderated multiple regression' might be profitably studied can be made quite large, and can be seen to include a number of situations of potential practical significance" (p. 210).

The concept of moderators has been utilized in a number of subsequent theories and moderated regression has been empirically investigated in a variety of settings. The steps of the traditional procedure for empirically determining the existence of a moderator effect are presented by Zedeck (1971). "The correlations, slopes, and standard error of estimates should be examined for the following three regression equations:

$$y = a + bx, \qquad [1$$

$$y = a + b_1x + b_2z \qquad [2$$

where z is the potential moderator but is treated as an independent predictor, and

$$y = a + b_1x + b_2z + b_3xz \qquad [3$$

(moderated regression equation). If equations 2 and 3 are significantly different from equation 1, but not from each other, then the variable is an independent predictor and not a moderator variable" (Zedeck, 1971, p. 304). These suggested steps have been followed whenever a moderated regression analysis has been conducted. Cohen (1968) and Cohen and Cohen (1975) show that moderated regression is one conceptualization of an interaction effect in the general linear model. They describe a hierarchical analysis for assessing the existence of an interaction that is equivalent to the procedure outlined above, i.e., one first determines the squared multiple correlation coefficient (R^2) for model 2 and then determines the increment in R^2 caused by adding the interaction term in model 3. The increment[1] is then tested for statistical significance, using model 3 error mean square.

In this hierarchical treatment, the moderator effect must account for dependent variable variance beyond that accounted for by the main effects alone. The main effects are, thus, given a preferential claim to any covariance that is shared by main effects and the moderator effect. Such preference may be unreasonable under the conditions that generally hold when a moderated regression analysis is conducted. The moderated regression analysis is usually done only if there is some theoretical basis to suspect the presence of a moderator effect. If such is the case, the researcher should attempt to use an analysis with reasonable statistical power, i.e., the probability of discovering an existing hypothesized effect. This article will demonstrate that traditional moderated regression analysis procedure, on the contrary, enhances the possibility of type II error, i.e., the failure to recognize the presence of an existing effect.

This subtle but critical flaw in the traditional analysis procedure can explain why the results of moderated regression analyses led Zedeck (1971) to state "In general, moderated regression has not been successful in improving predictions" (p. 302). Competitive demands for journal space and the tendencies of researchers to report only significant finds allows speculation that many instances of failure to find moderated regression have gone unreported. These failures to discover moderator effects and the disappointing characteristics of those effects that have been found result from the features of the traditional analysis procedure that are demonstrated in the data below.

Among the reported studies that have used moderated regression analysis, the results have been quite similar but the conclusions drawn from them have changed from one study to another. Investigators have based their conclusions on two statistical characteristics of the moderated relationship--the statistical significance of the increment due to the interaction term and the size of the increment.

Requirement of Statistical Significance

As examples of the moderated regression analysis procedure, Saunders (1956) presented three sets of data. In his first example, only one moderator effect was investigated. The increment in R^2 was .013, not significant. A second set of analyses tested the moderator effects of ten potential moderators. In this case, the increments ranged from zero to .025 with three of the ten reaching the .05 level of significance. His third set of demonstration data tested seven potential moderator effects. The increments ranged from zero to .017 with one of the effects significant at the .01 level. He concluded that a variable was operating as a moderator variable whenever the increment reached significance.

Jacobs and Solomon (in press) also concluded that a moderator effect had been shown when the R^2 increment was statistically significant. In their case 11 or 12 moderator effects were significant beyond the .05 level.[2] The increments in R^2 ranged from .009 to .104. In both the Saunders (1956) and Jacobs and Solomon (in press) studies the criterion for concluding that there is a moderator is the one stated by Zedeck, Cranny, Vale, and Smith (1971), "Presence of a moderator is thus indicated by the form of the equation, specifically by the significance of cross-product terms" (p. 239).

Requirement of a Sizable Increment

Stone (1976) and Stone, Mowday, and Porter (in press) drew a different conclusion from similar results. Stone (1976) showed an increment in R^2 of .016 significant at the .001 level. While acknowledging the statistical significance of the moderator effect, he went on to conclude from the size of the increment that "the gain in explained...variance is not marked when the... interaction term is introduced into the multiple prediction equation. The practical significance...appears, therefore, to be negligible" (p. 163). In a discussion of a finding of an increment in R^2 of .019, significant at the .01 level, Stone, Mowday, and Porter (in press) state that "the difference between the two multiple correlations while statistically significant,...is of negligible size" (p. 8). In both of these cases the authors have taken the size of the increment in R^2 as an index of the strength of the moderator effect. If a large increment is a legitimate requirement for drawing the conclusion that a moderator should be attended to, then one can wonder if any moderated regression analysis has ever produced a moderator effect that was not "negligible." Further, if the size of the increment in R^2 is taken as an indication of the strength of the moderator effect, the uniformly modest effects that have been reported in the literature would argue that moderator effects are not important tools in scientific endeavors, i.e., conceptual models that include moderator effects could just as well do without them. This article will argue that the size of the increment in R^2 cannot be interpreted in that fashion.

The research reported in this article was conducted to test the efficiency of the traditional moderated regression analysis procedures for discovering moderators. The study considers whether the existence or the strength of moderator effects is accurately reflected in the results from the traditional moderated regression analysis.

Method

Data Generation

In order to simulate data on which to perform the moderated regression analysis using a Monte Carlo approach, random normal deviates were generated according to the procedures of Box and Muller (1958). In all cases three variables, x, z, and e were constructed for each synthetic "individual." Variable x was treated in subsequent analyses as the independent variable, z was treated as the moderator variable, and e was used as error. The dependent variable, y, was constructed as described below for various cases. Except where it is noted in the definitions of the various cases given below, x and z had means ≈ 10 and standard deviations ≈ 1[3]; e had a mean ≈ 0 and a standard deviation ≈ 1.

Case One. In the first case the dependent variable was constructed so as to represent a situation with a moderator effect and some error: The generating model was $y = xz + 3$. One hundred samples, each with 100 subjects, were constructed. This case served as the basic moderator effect case, and other cases were generated for comparison purposes. In the additional cases, changes were made in the formula for generating the dependent variable.

Case Two. The second case represents a situation with greater unreliability in the measurement. This effect was accomplished by increasing the variance of the error term. The same model ($y = xz + e$) was used to generate the dependent variable. For this case the standard deviation of the error variable ≈ 5. Twenty samples, each with 100 subjects, were generated.

Case Three. The third case also used the basic model ($y = xz + e$) to create a dependent variable from a moderator effect. Unlike cases one and two, the independent variable and the moderator variable were constructed to be correlated. This relationship varied because of sample differences between .46 and 1.00 with a median value of .55. Twenty samples, each with 100 subjects, were generated.

Case Four. In the fourth case the dependent variable was built on a linear effects model rather than the interacting, moderator model. The generating model was $y = x + z + e$, thus specifying that y resulted from the additive combination of two unrelated variables plus error. Again, 20 samples of 100 subjects were constructed.

Case Five. The fifth case represents a situation with a dependent variable that is formed from a direct effect of the independent variable plus a moderator effect plus error. The constructive formula was $y = x + xz + e$. There were 20 samples of 100 subjects.

Case Six. In the final case the dependent variable is simply the independent variable plus error, and the formula for generating the dependent variable was $y = x + e$. There were 20 samples of 100 subjects each.

Table 1 summarizes the data generated for the six cases. Two hundred

---

Insert Table 1 About Here

---

samples were generated. The dependent variable, y, was constructed differently in the samples representing the six different cases. Each case represents a different model of underlying effects. In cases one, two, and three the dependent variable results from a moderator effect and random error. The dependent variable is an additive combination of the linear effects of the independent, moderator, and error variables in case four where there is no moderator effect. In case five a combination of a direct linear effect of the independent variable and a moderator effect (plus error) determine the dependent variable. Finally, case six presents a dependent variable that is a sum of the independent variable and error with no moderator effect.

Data Analysis

In each sample the traditional moderated regression analysis was conducted to see if that procedure would "discover" moderator effects where they had been included in the model and would fail to "discover" moderator effects where they were not present.[4] The increment in R^2 was determined in each sample as it would be in the traditional moderated regression analysis to represent the increase in predictability controlled by the moderator effect. The statistical significance of that increment was then tested using

$$F = \frac{96SS_{(xz|x,z)}}{SS_{(error)}},$$

where the numerator is the error degrees of freedom times the sum of squares of the moderator effect given the linear effects of the independent variable and the moderator variable, and the denominator is the sum of squares for error.[5]

Results

Statistical Significance

As shown in Table 2, the moderator effect was "discovered" by a requirement of statistical significance in Case 1 and Case 3. In both of those models all

- - - - - - - - - - - - - - - - - -
Insert Table 2 About Here
- - - - - - - - - - - - - - - - - -

of the samples provided an increment in R^2 for the moderator effect that was beyond that expected at the .05 level of significance. Though Case 2 and Case 5 also included a moderator effect in the formula that generated the dependent variable, the increment in R^2 did not reach statistically significant size in any of the samples of either of those cases. Case 2 differed from Case 1 in that the error component was greater in Case 2, i.e., there was more unreliability in the dependent variable. Case 5 differed from Case 1 by the inclusion of a direct relationship between the independent and dependent variables as well as the indirect, or moderated, relationship. The R^2 increment due to the moderator was not significant in any of the samples of the cases where the generating model did not include moderator effects, i.e., Case 4 and Case 6.

Size of the Increment

In all of the 200 samples the maximum increment in R^2 attributable to the moderator effect was .032 in one of the samples of Case 6. And there was not a moderator effect in the generating model for the dependent variable of Case 6! The minimum increment of zero was attained in three of the cases including Case 5 which involved a moderator effect. In general, none of the samples, either with or without actual moderator effects, provided large increments in R^2.

Success of Moderators in Non-Moderator Models

In the two cases where there is no moderator effect in the actual determination of the dependent variable, Case 4 and Case 6, a comparison was made between prediction by the moderator effect alone versus the true model. For Case 4, prediction of y by x plus z (the true model) provides a range of correlations over the 20 samples from .716 to .875 with a median correlation of .806. If the prediction of y is by the moderator term xz, alone, the correlations range from .708 to .869 with a median of .801. In other words, the moderator model predicts the additive data nearly as well as does the additive model. In two of the samples the multiplicative correlation actually exceeded the additive correlation.

For Case 6 the true model does better than the moderator term at predicting the dependent variable. When y is predicted from x alone (the true model) the correlations range from .640 to .803 with a median of .715. There is no overlap with the correlations using the interaction, xz, as the predictor. The moderator prediction gives a range of correlations from .359 to .619 with a median of .505.

Discussion

Using the traditional moderated regression analysis procedures the influence of a moderator effect was not shown even when the dependent variable was constructed to include a strong moderator effect. Cases 1, 2, and 3 created the dependent variable as a moderator effect plus some random error. Under those conditions Case 2 with a large error component did not demonstrate statistical significance for the moderator effect, and all three of the cases produced such small increments in R^2 attributable to the moderator that the moderator effect could have been called negligible if the size of the increment were interpreted as an indication of the strength of the effect. In Case 5, where the moderator influence is accompanied by both error and by a linear effect of the independent variable, there was neither statistical significance nor a sizable increment. That is, even in situations strongly biased in favor of discovering a moderator effect, i.e., a moderator effect has been used in the creation of the dependent variable, the traditional moderated regression analysis leads to the conclusion of "no moderator."

Why should such a result occur? Why should this analysis be so prone to overlook an effect that is in fact in the data? There are two influences that increase the likelihood of this type II error.

1. <u>The hierarchical nature of the multiple regression procedures robs the moderator term of covariance with the dependent variable.</u>

The traditional moderated regression analysis procedure first regresses the dependent variable on the linear effects of the independent variable and the potential moderator variable. The interaction term is then regressed on only the residual from that regression. The increment in R^2 which is used to judge both the existence and the strength of the moderator effect represents only the relationship with that part of the dependent variable variance that is unrelated to the two linear effects.

Any covariance with the dependent variable that is shared with the linear effects is automatically assigned to the linear effects. This implies a preference for the linear effects that is implicitly a theoretical hypothesis of the generating effects that have produced the dependent variable. This implied priority of the main effects should be supported by the researcher's theoretical understanding of the relationships among the variables; it cannot be accepted simply because the hierarchical analysis has traditionally proceeded in that direction. The ordering of effects in the hierarchical regression analysis is arbitrary. With appropriate theoretical justification the data analyst can, as validly, first assess the variance attributable to the moderator effect, and then determine whether the main effects make a significant and sizable addition to the variance accounted for. The point is, that the decision of the order in which effects are assessed is one that the researcher must support theoretically. Because the order of the removal of variance due to effects is an expression of a theoretical preference, the investigator cannot abnegate the responsibility for this decision on the grounds of tradition. This decision requires, not just blind application of techniques, but scientific judgment and justification.

2. <u>The linear regression model is a robust method for accounting for variance</u>.

Even if the prediction equation is an imperfect model of the process that generated the data, the linear regression model can often capture a great deal of the variance. The problem of using correlational procedures to assess the appropriateness of an hypothesized model has been discussed in the literature (Alf & Abrahams, 1974; Birnbaum, 1973, 1974; Rorer, 1974). Watson (1972) has demonstrated that this same problem can occur in the analysis of variance. He showed that data generated from an interaction might be accounted for by significant main effects leaving insignificant variance to be accounted for by the interaction.

In a demonstration similar to the one presented in this article Rorer (Note 1) used a linear regression model to replicate the decisions that had been made with several different decision strategies from constructed (synthesized) data. Using 11 different decision strategies that included linear, curvilinear, configural, sequential and categorical processes he was able to closely approximate the decisions of the real functions with a simple linear function. Discussing a hierarchical process for drawing conclusions that is the same as the hierarchical strategy of the traditional moderated regression analysis he states, "These results indicate vividly that it is difficult to infer nonlinearity, even when it exists" (p. 12). "These results show why the search for moderator variables has been so fruitless, just as much as they show why human judges have been unable to improve upon actuarial prediction by means of their purported ability to recognize and use patterned or unusual relationships. Even if such relationships exist, their incorporation into the decision strategy, be it actuarial or subjective, is not going to result in much improvement over the linear regression function in either case" (p. 13). The linear regression model is robust enough to capture much of the predictable variance of a dependent variable even if that dependent variable sprang from other than linear origins.

The critical distinction for the problem addressed in this paper is the difference between science and application. If a research has only the applied purpose of determining or demonstrating how variance can be accounted for, a statistical data analysis can provide answers. However, if the research has the scientific purpose of discovering or confirming an underlying model or generating process that produced the data, then traditional moderated regression analysis is inadequate for the task. The scientific question may be answered in part by a data analysis if the results demonstrate that a model is <u>in</u>compatible with the data, but the data analysis cannot choose between alternative models that all fit the data. For example, if y is predicted equally well by x + z and by xz, the data analysis is neutral as to choice. The selection of one model over the other rests with the rational scientific judgment and preference of the researcher.

There are viable theoretical contents that may lead a researcher to support a moderator effect as the correct model for his/her data. In his presentation of the moderated regression analysis Saunders (1956) proposed examples where a moderator effect was conceptually supportable. He included such examples as using insight as a moderator of the relationship between self reports and more objective measures of personality traits and using emotional stability as a moderator of the relationship between academic ability measures and academic success. Another interactive model that has been presented with elaborate theoretical justifications is expectancy theory (Staw, 1976; Vroom, 1964). Researchers in that area are likely to choose the multiplicative expectancy model for explanatory use even when an additive model is equally successful at accounting for variance. Their preference would be based on the rational depiction of the relationship among the variables that is afforded by the expectancy theory. Blood (1977) presents a model of the operation of the cognitive process of self rewarding on work performance. The model includes five variables acting as moderators. The logic of interactive relationships is preferred for the model because of the nature of the variables involved. This theoretical preference is rationally justified.

The issue of theoretical parsimony is not involved in the choice between a linear model and a moderator model. Whether two main effects or one interaction effect is the more parsimonious explanation is a matter of taste. Some people will prefer an additive model and other will elect the multiplicative, but it is not clear that one is simpler than the other. In addition to which, the principle of parsimony is used to choose between theories when other considerations are equal. If other considerations lead to its preference, one may be justified in choosing a less parsimonious model over a more parsimonious one.

This leaves us with the important task of suggesting how a researcher should proceed to assess the strength of a moderator effect. It there are theoretical reasons to support a hypothesis of a moderator effect, the dependent variable should be directly regressed on the cross-product of the independent variable and the potential moderator,

$$y = xz. \qquad [4$$

Then if desired, the additional contribution of the main effects can be assessed by determining the size and significance of their increment to the squared multiple correlation. That is, the hierarchical regression procedure should proceed in exactly the reverse order from the traditional moderated regression analysis procedure in those cases where a moderator effect is theoretically justified (see Cohen and Cohen, 1975 for analysis procedures).

There may be some cases where theory will suggest that the independent variable will influence the dependent variable partly through a main effect and partly through a moderated effect (as in Case 5). In that event, a researcher may wish to assess the size and significance of the combined main and moderator effects by the regression of

$$y = x + xz. \qquad [5$$

Should this analysis be used, caution should be exercised in interpreting the multiple correlation weights. Because of colinearity influences these will <u>not</u> indicate the relative contributions of the main and moderator effects (see Darlington, 1968; Cohen and Cohen, 1975).

A potential problem with these suggested procedures is that they have the possibility of also encouraging Type II error. If a model is underfit, true relationships can go undetected due to overestimation of the error term (Johnston, 1972). Variance that is uniquely related to the excluded variables is added to the error variance. This means, for example, that if a model of the form of [4 or [5 were used when the true (but unknown) model is [3, then the real moderator effect could remain statistically insignificant because of this bias. This problem exists whenever a hierarchical regression procedure is used and whenever the model in use may have excluded a variable that controls unique variance. This potential bias did not cause a problem in the present data, and it appears to be a less severe disturbance than the traditional moderated regression analysis procedure.

Whatever the theoretical predispositions of the investigator, an analysis should be chosen such that it is possible to confirm it, i.e., the analysis should not virtually guarantee type II error. The theory should guide the *analysis, not the reverse.* In the hierarchical analysis traditionally used to discern moderated regression, it is not possible to rule out a moderator as a generating factor for the dependent variable by showing that the main effects alone can account for most of the variance. Thoughtlessly following the traditional analytic procedures cannot replace the exercise of scientific judgment based on carefully drawn theory.

Reference Note

1. Rorer, L. G. *A circuitous route to bootstrapping selection procedures* (Research Bulletin Vol. 12, No. 9). Eugene, Ore.: Oregon Research Institute, 1972.

References

Alf, E. F., & Abrahams, N. M. Let's give the devil his due: A response to Birnbaum. Psychological Bulletin, 1974, 81, 72-73.

Birnbaum, M. H. The devil rides again: Correlation as an index of fit. Psychological Bulletin, 1973, 79, 239-242.

Birnbaum, M. H. Reply to the devil's advocates: Don't confound model testing and measurement. Psychological Bulletin, 1974, 81, 854-859.

Blood, M. R. Organizational control of performance through self rewarding. In King, B. T., Streufert, S. S., and Fiedler, F. E. (Eds.), Managerial Control and Organizational Democracy. Washington, D. C.: Victor Winston and Sons, 1977.

Box, G. E. P., & Muller, M. E. A note on the generation of random normal deviates. Annals of Mathematical Statistics, 1958, 29, 610-611.

Cohen, J. Multiple regression as a general data-analytic system. Psychological Bulletin, 1968, 70, 426-433.

Cohen, J., & Cohen, P. Applied multiple regression/correlation analysis for the behavioral sciences. Hillsdale, N. J.: Lawrence Erlbaum Associates, 1975.

Darlington, R. B. Multiple regression in psychological research and practice. Psychological Bulletin, 1968, 69, 161-182.

Jacobs, R., & Solomon, T. Strategies for the prediction of job performance. Journal of Applied Psychology, in press.

Johnston, J. Econometric methods, 2nd ed. New York: McGraw-Hill, 1972.

Rorer, L. G. "What, can the devill speake true?" Psychological Bulletin, 1974, 81, 355-357.

Saunders, D. R. Moderator variables in prediction. Educational and Psychological Measurement, 1956, 16, 209-222.

Staw, B. M. Instrinsic and extrinsic motivation. Morristown, N. J.: General Learning Press, 1975.

Stone, E. F. The moderating effect of work-related values on the job scope-job satisfaction relationship. Organizational Behavior and Human Performance, 1976, 15, 147-167.

Stone, E. F., Mowday, R. T., & Porter, L. W. Higher-order need strengths as moderators of the job scope-job satisfaction relationship. Journal of Applied Psychology, in press.

References (Con'td.)

Vroom, V. H. Work and motivation. New York: Wiley, 1964.

Watson, J. S. We assess lawfulness, but God knows what the law is. Proceedings of the 80th Annual Convention of the American Psychological Association, 1972, 7, 139-140. (Summary)

Zedeck, S. Problems with the use of "moderator" variables. Psychological Bulletin, 1971, 76, 295-310.

Zedeck, S., Cranny, C. J., Vale, C. A., and Smith, P. C. Comparison of "joint moderators" in three prediction techniques. Journal of Applied Psychology, 1971, 55, 234-240.

Footnotes

[1]This increment is called the squared semipartial correlation coefficient by Cohen and Cohen (1975) and the "Usefulness" index by Darlington (1968).

[2]Because of interdependencies among the variables, these were not 12 independent effects.

[3]It is important to note that the distributions of independent and moderator variables included only positive numbers. This is usual for social science data. Because of the manner of construction of y, the results would be changed if x and z took on both positive and negative values.

[4]The authors wish to thank Mark Elliott and Julie Bierer for their help with the data generation and analysis for this study.

[5]This is the sum of squares for error of this prediction model, not sum of squares for the "e" term used in generating the dependent variable.

Table 1

Structure of the Simulated Samples

Case	Number of Samples	Subjects per Sample	Generating Formula	Special Features
1	100	100	$y = xz + e$	
2	20	100	$y = xz + e$	$Se = 5Sx = 5Sz$
3	20	100	$y = xz + e$	$mdnr_{xz} = .55$
4	20	100	$y = x + z + e$	
5	20	100	$y = x + xz + e$	
6	20	100	$y = x + e$	

Table 2

Results of Traditional Moderated Regression Analysis

Case	Average Increment in R^2	Minimum Increment in R^2	Maximum Increment in R^2	Increments Significant at .05 level
1	.005	.002	.009	100 of 100
2	.006	.001	.022	0 of 20
3	.006	.003	.010	20 of 20
4	.004	.000	.015	0 of 20
5	.003	.000	.016	0 of 20
6	.008	.000	.032	0 of 20

Distribution List

Office of Naval Research (3 copies)
(Code 452)
800 N. Quincy St.
Arlington, VA 22217

Director
U. S. Naval Research Laboratory (6 copies)
Washington, DC 20390
ATTN: Technical Information Division

Defense Documentation Center (12 copies)
Building 5
Cameron Station
Alexandria, VA 22314

Library, Code 2029 (6 copies)
U. S. Naval Research Laboratory
Washington, DC 20390

Science & Technology Division
Library of Congress
Washington, DC 20540

Director
ONR Branch Office
495 Summer St.
Boston, MA 02210

Psychologist
ONR Branch Office
495 Summer St.
Boston, MA 02210

Director
ONR Branch Office
536 S. Clark St.
Chicago, IL 60605

Director
ONR Branch Office
1030 E. Green St.
Pasadena, CA 91106

Psychologist
ONR Branch Office
1030 E. Green St.
Pasadena, CA 91106

Research Psychologist
ONR Branch Office
536 S. Clark St.
Chicago, IL 60605

Dr. Earl A. Alluisi
Old Dominion University Res. Foundation
Norfolk, VA 23508

Dr. Judith Daly
Decisions & Designs, Inc.
Suite 100
8400 Westpark Dr.
McLean, VA 22101

Dr. James A. Bayton
Department of Psychology
Howard University
Washington, DC 20001

Dr. H. Russell Bernard
Dept. of Sociology & Anthropology
West Virginia University
Morgantown, W. VA 26506

Dr. Arthur Blaiwes
Naval Training Equipment Center
Orlando, FL 32813

Dr. Milton R. Blood
School of Business
Georgia Institute of Technology
Atlanta, GA 30332

Dr. Davis B. Bobrow
University of Maryland
Department of Government & Politics
College Park, MD 20742

Dr. David G. Bowers
Institute for Social Research
University of Michigan
Ann Arbor, MI 48106

Dr. John J. Collins
Vice President
Essex Corporation
6305 Caminito Estrellado
San Diego, CA 92120

Dr. Harry R. Day
University City Science Center
Center for Social Development
3624 Science Center
Philadelphia, PA 19104

Dr. C. Brooklyn Derr
Associate Professor, Code 55
Naval Post Graduate School
Monterey, CA 93940

Distribution List (continued)

Dr. George T. Duncan
Carnegie-Mellon University
5000 Forbes Ave.
Pittsburgh, PA 15213

Dr. Samuel L. Gaertner
Department of Psychology
University of Delaware
220 Wolf Hall
Newark, DE 19711

Dr. William E. Gaymon
Suite 200
1055 Thomas Jefferson St., NW
Washington, DC 20007

Dr. Paul S. Goodman
Graduate School of Industrial Admin.
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. J. Richard Hackman
Administrative Sciences
Yale University
56 Hillhouse Ave.
New Haven, CT 06520

Dr. Leo A. Hazlewood
CACI, Inc.
1815 Fort Myer Dr.
Arlington, VA 22209

Dr. Edwin Hollander
Department of Psychology
State University of New York at Buffalo
4230 Ridge Lea Rd.
Buffalo, NY 14226

Mr. Daniel F. Huck
General Research Corp.
Westgate Research Park
McLean, VA 22101

Dr. Charles L. Hulin
Department of Psychology
University of Illinois
Champaign, IL 61820

Dr. Rudi Klauss
Syracuse University
Public Administration Dept.
Maxwell School
Syracuse, NY 13210

Dr. Edward E. Lawler
Battelle Human Affairs Research Centers
4000 N.E. 41st St.
P.O. Box 5395
Seattle, WA 98105

Dr. Arie Y. Lewin
Duke University
Duke Station
Durham, NC 27706

Dr. Morgan W. McCall, Jr.
Center for Creative Leadership
5000 Laurinda Dr.
P.O. Box P-1
Greensboro, NC 27402

Dr. Terence R. Mitchell
School of Business Administration
University of Washington
Seattle, WA 98195

Dr. William H. Mobley
College of Business Administration
University of South Carolina
Columbia, SC 29208

Dr. Thomas D. Morris
The Brookings Institution
1775 Massachusetts Ave., NW
Washington, DC 20036

Dr. James P. Murphy
National Analysts
A Division of Booz-Allen & Hamilton, Inc.
400 Market St.
Philadelphia, PA 19106

Dr. Peter G. Nordlie
Human Sciences Research, Inc.
7710 Old Springhouse Rd.
McLean, VA 22101

Dr. Herbert R. Northrup
Industrial Research Unit
University of Pennsylvania
Philadelphia, PA 19174

Dr. A. F. K. Organski
3068 Institute for Social Research
University of Michigan
Ann Arbor, MI 48104

Distribution List (continued)

Dr. Paul Pedersen
Society for Intercultural Education,
Training and Research
107 MIB, University of Pittsburgh
Pittsburgh, PA 15260

Dr. Manuel Ramirez
Systems and Evaluations
232 Swanton Blvd.
Santa Cruz, CA 95060

Dr. Irwin Sarason
Department of Psychology
University of Washington
Seattle, WA 98195

Dr. S. B. Sells
Texas Christian University
Fort Worth, TX 76129

Dr. H. Wallace Sinaiko
Program Director
Manpower Research & Advisory Services
Smithsonian Institution
801 N. Pitt St. - Suite 120
Alexandria, VA 22314

Mrs. Alice I. Snyder
Mental Health Clinic
Naval Regional Medical Center
Pearl Harbor
FPO San Francisco, CA 96610

Dr. Richard Steers
Graduate School of Management & Business
University of Oregon
Eugene, OR 97403

Dr. Victor H. Vroom
School of Organizational Management
Yale University
56 Hillhouse Ave.
New Haven, CT 06520

Dr. Abraham R. Wagner
Analytical Assessments Corp.
357 South Robertson Blvd.
Beverly Hills, CA 90211

Dr. J. Wilkenfeld
Department of Government & Politics
College Park, MD 20742

AFOSR/NL
Bldg., 410
Bolling AFB
Washington, DC 20332

Military Assistant for Human Resources
OAD (E&LS) ODDR&E
Pentagon 3D129
Washington, DC 20301

HQ, USAF
AFMPC/DPMYP
Randolph AFB, TX 78148

Air University Library/LSE-8110
Maxwell AFB, AL 36112

Office of the Deputy Chief of Staff
for Personnel, Research Office
ATTN: DAPE-PBR
Washington, DC 20310

Chief, Plans & Operations Office
USA Research Institute for the
Behavioral & Social Sciences
Room 278
1300 Wilson Blvd.
Arlington, VA 22209

Army Research Institute (2 cys)
Commonwealth Bldg.
1300 Wilson Blvd.
Rosslyn, VA 22209

ARI Field Unit - Leavenworth
P.O. Box 3122
Fort Leavenworth, KS 66027

Headquarters, Forces Command
AFPE-HR
Ft. McPherson
Atlanta, GA 30330

Dr. A. L. Slafkosky
Code RD-1
HQ US Marine Corps
Washington, DC 20380

Commandant of the Marine Corps.
(Code MPI-20)
Washington, DC 20380

Distribution List (continued)

Chief, Psychological Research Branch
US Coast Guard (G-P-1/62)
400 7th St., SW
Washington, DC 20590

Chief of Naval Personnel
Assistant for Research Liaison (Pers-Or)
Washington, DC 20370

Bureau of Naval Personnel (Pers 6)
Assistant Chief of Naval Personnel for
Human Resource Management
Washington, DC 20370

Bureau of Naval Personnel (Pers-6a3)
Human Resource Management Financial Office
Washington, DC 20370

CDR Paul D. Nelson, MSC, USN
Head, Human Performance Division (Code 44)
Navy Medical R&D Command
Bethesda, MD 20014

Assistant Officer in Charge
Naval Internal Relations Activity
Pentagon, Room 2E329
Washington, DC 20350

Naval Postgraduate School
Monterey, CA 93940
ATTN: Library (Code 2124)

Professor John Senger
Operations Research & Administration
Sciences
Naval Postgraduate School
Monterey, CA 93940

Head, Human Factors Engineering Branch
(1242)
USN Pacific Missile Center
Pt. Mugu, CA 93042

Training Officer
Human Resource Management Center
San Diego, CA 92133 NTC

Scientific Director
Naval Health Research Center
San Diego, CA 92152

Navy Personnel R&D Center (5 cys)
Code 01
San Diego, CA 92152

Commanding Officer
Naval Submarine Medical Research Lab.
Naval Submarine Base New London, Box 900
Groton, CT 06340

Commanding Officer
Naval Training Equipment Center
Technical Library
Orlando, FL 32813

Naval Aerospace Medical Research Lab.
(Code L5)
Naval Aerospace Medical Center
Pensacola, FL 32512

Lt. Rebecca G. Vinson, U.S.N.
Navy Recruiting District, Boston
575 Technology Square
Cambridge, MA 02139

Chief, Naval Technical Training
NAS Memphis (75)
Millington, TN 38054
ATTN: Mr. Tom Warrick, N622

Human Resource Management Center
Box 23
FPO New York 09510

Human Resource Management Center, Norfoll
5621-23 Tidewater Drive
Norfolk, VA 23511

Human Resource Management Center
Bldg., 304
Naval Training Center
San Diego, CA 92133

Office of Naval Research (Code 200)
Arlington, VA 22217

ACOS Research & Program Development
Chief of Naval Education & Training (N-5
Naval Air Station
Pensacola, FL 32508

Human Resource Management Center
Pearl Harbor
FPO San Francisco, CA 96601

Human Resource Management School
Naval Air Station Memphis (96)
Millington, TN 38054

Distribution List (continued)

Director, Programs Development Division
(Code N-35)
Chief of Naval Education & Training
Naval Air Station
Pensacola, FL 32508

Capt. Charles Baldwin
Bureau of Naval Personnel
Pers 65
Washington, DC 20370

Director, Human Resource Training Department
Naval Amphibious School
Little Creek
Naval Amphibious Base
Norfolk, VA 23521

Navy Material Command
Employee Development Office (Code SA-65)
Room 140 Jefferson Plaza, Bldg., #2
1429 Jeff Davis Highway
Arlington, VA 20360

Human Resource Management Center, Washington
Washington, DC 20370

Dr. Robert B. Tebbs
Franklin University
201 South Grant Ave.
Columbus, OH 43215

HumRRO (ATTN: Library)
300 N. Washington St.
Alexandria, VA 22314

Director, Columbus Office
HumRRO Central Division, Suite 23
2601 Cross Country Dr.
Columbus, GA 31906

Office of the Air Attache
Embassy of Australia
1601 Massachusetts Ave., NW
Washington, DC 20036

Scientific Information Officer
British Embassy
3100 Massachusetts Ave., NW
Washington, DC 20008

Canadian Defense Liaison Staff, Washington
2450 Massachusetts Ave., NW
Washington, DC 20008
ATTN: Chief, Defense Research

Mr. Luigi Petrullo
2431 N. Edgewood St.
Arlington, VA 22207

Dr. John J. Collins
6305 Caminito Estrellado
San Diego, CA 92120